LOAN LOSS PROVISIONING IN COMMUNITY BANKS – A STUDY WITH NEW COMMUNITY BANKING DATA

A Thesis Submitted to

the College of Graduate and Postdoctoral Studies

in Partial Fulfillment of the Requirements for the degree of

Master of Science in Finance in

the Edwards School of Business

University of Saskatchewan, Saskatoon

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ABSTRACT

We use a new community banking data set constructed by Federal Deposits Insurance Corporation to examine loan loss provisioning in U.S. community banks. We find that community banks use loan loss provisions to smooth their income. In addition, we find community banks employ a dynamic income smoothing process using loan charge-offs to keep allowance account flat overtime. Our evidence shows that loan loss provision is responsive to variations in local economic conditions. We do not find evidence that loan loss provisioning differs between standalone community banks and the community banks that are part of bank holding companies. Specifically, we do not find evidence that community banks that are part of bank holding companies are less aggressive in income smoothing than standalone community banks. However, our study provides evidence that traded community banks do not indulge in income smoothing. One possible explanation could be the stricter scrutiny from regulators, investors and analysts. Our study complements to the bank income smoothing literature by investigating the income smoothing of community banks.

Key Words: loan loss provisioning, income smoothing, community bank

ACKNOWLEDGEMENT

I would first like to express my gratitude to my supervisors, Dr. Abdullah Mamun and Dr. Dev Mishra for their help and guidance. I could not complete the thesis without their useful comments and engagement. I would also like to thank Dr. Craig Wilson, Dr. Min Maung and Dr. Anand Jha for their constructive suggestions. Furthermore, I would like to thank my family, thanks for their understanding and support through the entire process, financially and mentally. Last but not the least, I would like to thank University of Saskatchewan for providing me such a great experience in learning.

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CHAPTER 1

INTRODUCTION

Loan loss provision reflects bank managers' estimation of possible future loss of loan portfolios due to unrecovered loans. It is the most important and the largest accrual for banks (Kanagaretnam et al., 2010). As loan loss provisions are directly charged against income statement before estimating net income, and managers have discretion in determining timing and amount for this account; as such loan loss provisions are closely related to transparency and timely accounting information in banks. However, literature overwhelmingly finds the loan loss provision is used as a major tool for banks to manipulate their earnings (Greenwalt and Sinkey, 1988; Wahlen, 1994; Collins et al., 1995; Beatty et al., 1995; Ahmed et al., 1999; Liu and Ryan, 1995, 2006; Laeven and Majnoni, 2003; Bikker and Metzemakers, 2005; Kanagaretnam et al., 2003; Fonseca and Gonzalez, 2008; Ryan and Keely, 2013).

Income smoothing literature to date has examined loan loss provisioning for large commercial banks and bank holding companies. For instance, Kim and Kross (1998), Kanagaretnam et al. (2010), Liu and Ryan (2006), Beck and Narayanamoorthy (2013) investigate into bank holding companies; Bushman and Williams (2012) examine both private and public banks with assets in excess of 5 billion dollars. Community banks, which are on average smaller in size and are not usually publicly traded, practically remain thinly covered in the existing literature. It might be that the researchers have tough time finding a practical way of defining community banks. There is no study to our knowledge that investigates the income smoothing behavior of community banks. Prior studies on community banks often use a 1 billion size cut-off for defining community banks (DeYoung et al., 2004). However, size is not a good proxy since it is just loosely related to community banks. Not to mention a fixed size cut-off does not consider the inflation and the growth of banking industry. Logically, factors such as primary engagement in traditional banking business and operations spanning limited geographic region merit consideration in identifying community banks. Accordingly, the Federal Deposit Insurance Corporation (FDIC) community banking study[1] (2012) uses a multidimensional approach to defining community banks, given their access to rich sources of data on community banks. FDIC study defines community banks by imposing geographic limits, business type limits, and multiple

[1] See FDIC community banking study at https://www.fdic.gov/regulations/resources/cbi/study.html

size limits. These limits allow inclusion of large community banks, which have been excluded in previous studies that uses community bank sample. More importantly, by definition FDIC sample of community banks includes banks which are expected to be more responsive to shocks to local economy. The newly constructed FDIC sample of community banks accounts for 94 percent of all bank organizations and the majority of deposits of these banks come from non-metropolitan area.

In this study, we use the new definition proposed by FDIC and try to gain understanding of earning management behavior of community banks. To our knowledge, this is the first study that uses this definition to construct the sample to examine income-smoothing behavior of community banks. Income smoothing can be quite different and may serve a very different purpose in community banks compared to large commercial banks. First, the motivations behind income smoothing can be different at community banks. As opposed to commercial banks, most of community banks are not publicly traded. As a result, in contrast to commercial banks, community banks do not need to be concerned about meeting analysts' forecasts. Second, according to FDIC community banking study (2012), compared to non-community banks, community banks less frequently raise external financing to operate their business. As a general practice, the retained earnings support their business, exceptions can be significant expansion in their business or significant financial loss. Therefore, community banks might have less incentive to lower their cost of capital through income smoothing. Third, because community banks are locally operated, the loan loss provisions of such banks are sensitive to the variation in local economy. On the contrary, large commercial banks may have operation across states, nationwide, or even globally, thus enjoy significant geographic diversification in loan portfolio. Therefore, the loan loss provisions for commercial banks are less sensitive to local economic conditions. Fourth, Liu and Ryan (2006) point out that banks accelerate the loan loss provisions of homogenous loans (consumer loans) during boom and delay loan loss provisions of heterogenous loans (commercial loans) during recession. Community banks mainly engage in traditional banking, consequently, they have fewer commercial loans and more consumer loans compared to those of commercial banks. This can be another reason that community banks would behave differently in loan loss provisioning than commercial banks. This study complements the studies which examine the smoothing behavior of bank holding companies and traded banks. Because community banks play pivotal role in the development and growth of small businesses and non-metropolitan economies, they are unique and essential to U.S. economy. Therefore, our study has implications for regulators in designing and implementing policies affecting community banks.

We attempt to address four questions. First, since motivations can be different in community banks, we investigate whether income smoothing through loan loss provisioning exists in community banks. Second, different from previous researches using macroeconomic variables in loan loss provisioning models for commercial banks, we examine whether local economic information affects the loan loss provisioning in community banks. Third, since the new definition includes large bank holding companies as community banks, we want to know whether there is a difference in loan loss provisioning between community banks that are part of bank holding companies and community banks that are not. Fourth, dynamic income smoothing is proposed by Liu and Ryan (2006) as a way for banks to obscure their income-smoothing behavior and keeping a smooth loan loss allowance. We examine whether dynamic income smoothing also exists in community banks.

This study proceeds as follows. Section 1 documents the prior related literature; Section 2 and 3 represents our hypothesis and data; Section 4 describes methodology used in this study; Section 5 reports the empirical results; and Section 6 concludes.

CHAPTER 2

LITERATURE REVIEW

2.1 Loan Loss Provisioning and Income Smoothing

Literature puts forward many reasons for banks to manipulate loan loss provisioning. Three main reasons that dominate the literature are a) to reduce the volatility of income, and as a result, banks can lower their cost of capital (Greenwald and Sinkey, 1988; Wahlen, 1994; Laeven and Majnoni, 2003); b) capital management (Kim and Kross, 1998; Ahamed et al., 1999; Laeven and Majnoni, 2003) and c) signaling financial strength in the future (Wahlen, 1994; Beaver and Engel, 1996). Other reasons include meeting analysts' forecasts (Galai et al., 2003); managerial incentives (Lambert, 1984; Joyce, 1996); and tax incentives (Rozycki, 1997).

With respect to the signaling theory, Wahlen (1994) report bank managers increase discretionary part of loan loss provisions when they expect stronger cash flows in the future. Because loan loss provisions reduce income, the managers are able to adjust their income based on their expectations. Apart from this, the study finds investors take an increase in discretionary loan loss provisions positively, because they believe banks convey private information through this behavior. Consistent with Wahlen (1994), Beaver and Engel (1996) examine how capital market react to discretionary and nondiscretionary loan loss provisions and report that investors view an increase in discretionary loan loss provisions positively and an increase in non-discretionary loan loss provisions negatively during 1985 to 1991. Ahamed et al. (1999), however, test the signaling theory using a different specification. Instead of running one-year ahead change in earnings on discretionary loan loss provisions, they regress loan loss provisions on one-year ahead change in earnings. Contrary to the findings of Wahlen (1994), Ahamed et al. (1999) find that one-year ahead change in earnings is significantly negatively associated with loan loss provisions. They suggest that studying different time-period might be the reason that they have a contrary result, since they rerun the regressions from Wahlen (1994) and find the same negative relationship between one-year ahead change in earnings and loan loss provisions during their study period.

Earning management literature is extensive. Collins et al. (1995) use bank-specific method and observe that loan loss provision is significantly positively associated with operating earnings before security gains and losses and other items. Ahmed et al. (1999) apply the loan loss provisioning model from Collins et al. (1995) and find that income-smoothing behavior exists in banks in the new capital regime when loan loss reserves do not qualify for tier 1 capital. Laeven and Majnoni (2003) in a multi-country sample of banks, find strong evidence of income smoothing in banks from four regions USA, Europe, Japan, Latin America, while they do not find evidence of income smoothing in Asian banks. Bikker and Metzemakers (2005) develop a loan loss provisioning model based on the works by Laeven and Majnoni (2003) and Cavallo and Majnoni (2002). Using a multi-country sample, Bikker and Metzemakers (2005) regress loan loss provisions on a lagged dependent variable and other determinants. They find a consistent income smoothing result. Liu and Ryan (2006) find profitable banks tend to be more aggressive in income smoothing during boom. One of the contributions of Liu and Ryan (2006) is that they assert loan charge-offs are discretionary and propose a dynamic income smoothing model. In an international sample of banks, Fonseca and Gonzalez (2008) add country effects and capital ratio to specifications used in Laeven and Majnoni (2003), additionally, they also use the level of loan loss reserves as a control variable and find significant evidence of income-smoothing behavior in banks. Similarly, in a cross-country sample of banks from 27 countries, Bushman and Williams (2012) also report that managers may use discretionary loan loss provisioning for income smoothing and dampen disciplinary risk-taking behavior of banks.

However, a small number of studies report no evidence of income smoothing. For example, Beatty et al. (1995) argue that capital management and earning management are jointly determined and report no evidence of income smoothing. Ahmed et al. (1999) do not find evidence of income smoothing until they adopt Collins et al. (1995) model. The primary reason for no evidence of income smoothing in these studies is that they focused on pre-BASEL period, for which the loan loss provisions are subtracted from income but added back to capital. Therefore, using sample from this period, it is difficult to separate earning management from capital management.

2.2 Bank Performance and Local Economic Conditions

Literature Finds mixed results on the relationship of bank performance and economic conditions. Meyer and Yeager (2001) examine whether local economic downturns affect small rural banks. By studying small banks under 300 million dollars in rural area, they find bank performance, measured by variables such as adjusted return on assets (ROA) and nonperforming loans to total loans, is significantly related to local economic conditions at state level, while not at county level. In contrast to the literature that uses single economic indicator such as Gross State

Product (GSP), Daly et al. (2003) use a composite index by Crone (2002) and find the state-level composite economic index robustly explains the bank performance measured by nonperforming loans. However, Yeager (2004) compare community banks which suffered through economic downturns with those which did not suffer economic shocks, and he conclude that economic shocks are not the contributor to the decline of community banks. Furlong and Krainer (2007) provide a new perspective in the relationship between local economic condition and bank performance by suggesting not only studying the average effect of local economic condition on bank performance, but also on the distribution of bank performance. Using small banks under one billion dollars and state-level economic data, they conclude that community banks could act very positive or very negative to the same state-level economic shock, and the reason for this significant variation is the different natures of the shocks and different loan portfolios of banks.

2.3 Loan Loss Provisioning Models

The minimum capital requirement under BASEL has raised concern regarding the procyclical effect to economy. Literature points out that during economic downturns, banks tend to provide less capital to the markets in order to reach the minimum capital requirement. This undesired effect of BASEL is expected to accelerate the deterioration of the economy during the downturns (Alistair and Elizabeth, 2001). The research of Laeven and Majnoni (2003) provides more insight into pro-cyclical effect of BASEL I. In a sample drawn from 45 counties around the world covering the period from 1988 to 1999, which includes at least one business cycle, Laeven and Majnoni (2003) use a bank-specific random effect model to test this question. In the model, the loan growth is used to control the bank-specific risk and the change in Gross Domestic Product (GDP) is used to control economic cycle. In addition, year dummies are also account for unknown time effects such as the changes in regulation. The study shows that loan loss provisions are significantly negatively associated with the loan growth, which is not desirable since loan loss provisions should increase with expanding credit. The change in GDP is significantly negatively associated with loan loss provisions, which indicates that the loan loss provision decisions are concurrent to the changes in the economy, and that the economic conditions are the major factors that managers take into account in determining the size of the loan loss provisions. Another important finding of Laeven and Majnoni (2003) is that banks with negative earnings tend to make larger loan loss provisions than banks with positive earnings, suggesting banks make more loan loss provisions at bust and therefore leave less capital available to the market, this behavior of banks deteriorates the procyclical problem. Agénora and Silva (2017) find that dynamic loan loss provisioning which uses future information can be an effective solution to the procyclical problem.

Liu and Ryan (1995) find in economic downturns, banks are able to delay loan loss provisions of heterogeneous loans rather than homogeneous loans. However, Liu and Ryan (2006) find that in economic upturns, banks behave differently in their treatment of loan loss provisions. More specifically, they find banks accelerate the loan loss provisions for homogeneous loans instead of heterogeneous loans and use charge-offs and recoveries of homogenous loans to keep their loan loss allowance flat during boom. Liu and Ryan are the first to propose that charge-offs are discretionary. Liu and Ryan regress a fixed time effect model based on the model by Ahmed et al. (1999) and deflate variables by assets at beginning of the year. Compared with the model by Ahmed et al. (1999), Liu and Ryan's model add a dummy takes 1 when a bank has above-median ROA, the percentage of homogeneous loans over total loans, and interactions of these two variables with earnings. These two interactions are significantly positive, providing evidence that banks which are more profitable and have more homogenous loans indulge into income smoothing during economic upturns. Liu and Ryan also find a significantly positive coefficient on earnings, consistent with the literature that reports significant income smoothing at banks.

Kanagaretnam et al. (2010) investigate the auditor independence in the banking industry. Specifically, they investigate the relationship between unexpected audit fee and abnormal loan loss provisions. In a sample of banks covering a period from 2000 to 2006, Kanagaretnam et al. use two stage regressions to test this research question. The first stage uses loan loss provisioning model to obtain abnormal loan loss provisions, and the second stage estimates the relationship between abnormal loan loss provisions and abnormal audit fee. They develop their loan loss provisioning model by integrating models from Wahlen (1994) and Kanagaretnam et al. (2004). Control variables in the loan loss provisioning model of Kanagaretnam et al. (2010) include year beginning value of loan loss allowance, non-performing loans; change in the non-performing loans; net loan charge-offs; loan growth; total outstanding loans; loans categories and year controls. Besides, they deflate all the variables by asset at beginning of the year. Compared with previous models, their model controls for more factors and is more comprehensive.

It has been argued that using incurred loss model to estimate loan loss provisions has potential procyclical effect. For example, using incurred loss information, such as nonperforming loans that are recorded when loans default over 90 days, causes a delay in the recognition of loan loss provisions. Bushman and Williams (2012) examine the possible consequences of discretion in loan loss provisions and forward-looking loan loss provisioning models in the context of risk-taking. Their sample consists of both private and public banks from 27 countries from 1995 to 2006. Including the change in the nonperforming loans at the following year, Bushman and Williams test income-smoothing behavior in a forward-looking model. They control for concurrent and past two year's change of nonperforming loans, capital ratio, size, and the change in the GDP, and their results show a significant positive loading for earnings, which indicates income-smoothing behavior, and a significantly positive loading for forward-nonperforming loans, suggesting loan loss provisioning is forward-looking.

Beck and Narayanamoorthy (2013) investigate in effect of Securities and Exchange Commission (SEC)'s new guidance, Staff Accounting Bulletin (SAB) 102 and the policy statement of Federal Financial Institutions Examination Council (FFIEC) (2001) on banks informativeness. They propose that SAB 102 and FFIEC (2001) policy statement encourage banks to rely more on historical charge-offs and less on nonperforming loans in determining the size of loan loss provision. And they put forward that these policies improve the informativeness of loan loss allowance (the association between loan loss allowance and future charge-offs) in strong banks which have better profitability and capital ratios. Beck and Narayanamoorthy regress both loan loss allowance and loan loss provisions models. In the loan loss provisioning model, they control for change in nonperforming loans, charge-offs, loans categories, size, change in the unemployment rate, and the return on the Case-Shiller real estate index. Using bank holding companies' quarterly data from 1992 to 2008, Beck and Narayanamoorthy find effects of the policies are as expected.

CHAPTER 3

HYPOTHESES

Prior studies focused on relatively larger commercial banks and documented that the coefficients on banks' earnings are significantly positive in different loan loss provisioning models (Collins et al., 1995; Laeven and Majnoni, 2003; Bikker and Metzemakers, 2005; Liu and Ryan, 2006; Fonseca and Gonzalez, 2008), suggesting significant evidence of income smoothing. However, to our knowledge, income-smoothing behavior of community banks remains unexplored in academic literature. Unlike large commercial banks, most of community banks are not publicly traded. According to FDIC community banking study (2012), till 2011, around 84% of community banks are not publicly traded, among the rest, only 5% of community banks are traded in major exchanges. As a result, they may have less incentive to create a stable income to lower their cost of capital, to signal future financial strength, and to meet analysts' forecasts, suggesting little incentive to use loan loss provisions for income smoothing. Nevertheless, other motivations for income smoothing, such as agency problems, in particular managerial incentives and design of executive compensation packages, may still be instrumental in the use of loan loss provisions for income smoothing at community banks. Therefore, we propose that use of loan loss provisions for income smoothing exists in community banks. If income-smoothing behavior does exist in community banks, we should observe significantly positive coefficients on earnings in loan loss provisioning models.

H1: In community banks, the relation between loan loss provisions and contemptuous income is significantly positive.

Prior studies on income-smoothing behavior are not able to compare the standalone community banks with community banks that are part of bank holding companies in loan loss provisioning, because those studies generally examine large commercial banks or bank holding companies. However, in our bank sample, we include community banks that are part of bank holding companies and community banks that are standalone. Therefore, we are able to test the bank holding company effect by hypothesizing that community banks which are part of bank holding companies smooth less income than standalone community banks. We hypothesize it for two reasons. Community banks that are part of bank holding companies have better access to resources at economic downturns than standalone community banks, because the better performing units may prop the poorly performing units during the downturns. Since a bank holding company can own several banks, the business of a bank holding company is expected to be more diversified than a standalone community bank. As a result, community banks that are part of bank holding companies have less incentive to create an excess reserve for economic downturns. In addition, the community banks that are part of the bank holding company are more likely to be traded as such they may benefit from capital market scrutiny. In particular, the scrutiny of capital market regulatory bodies, such as SEC, the analysts and investors compared to the standalone community banks[2]. As such we hypothesize:

H2: Community banks that are part of bank holding companies may smooth income less aggressively than standalone community banks.

The relation between local economic conditions and community banks has been examined in a variety of studies and the results are mixed to date. For example, Daly et al. (2003) find the state-level composite index of economic performance, that includes multiple regional economic indicators, is very relevant to the bank performance such as nonperforming loans. However, Yeager (2004) conclude that the local economic downturn is not the reason for the demise of community banks. Consistent with Daly et al. (2003), we use the state-level composite index constructed by Crone (2002) to test the relation between local economic conditions and loan loss provisions in community banks.

Many studies include economic variables in loan loss provisioning models to examine noncommunity banks. Bushman and Williams (2012) find the loan loss provisions behave differently across countries, therefore they used percentage change in GDP, to control the macroeconomic conditions in cross-country data. Nevertheless, they do not find the percentage change in GDP loading with a significant coefficient in their loan loss provisioning regression. Beck and Narayanamoorthy (2013) adopt change in the unemployment rate and return on Case-Shiller index as two control variables in their loan loss provisioning model, and they find these two variables are significant in loan loss provisioning regressions. Because community banks are expected to be more connected with local economic activities, they are expected to be affected more by the variations in local economic conditions, as such the economic indicators that better reflect the local economic situation are naturally expected to have significant effect on the loan

[2] For instance, in late 1990s, SEC investigated into SunTrust bank for holding too much loan loss allowance for the purpose of income smoothing and forced the bank to reduce $100 million of its loan loss allowance. Later, SEC issued a new guidance SAB 102 for loan loss allowance in 2001. (Sutton 1997; Levitt 1998; Wall and Koch 2000)

loss provisioning of community banks. This suggests that state-level economic indicators would be strongly loaded in the loan loss provisioning regressions for community banks. If community banks account for local economic conditions in estimating loan loss provisions, we expect to observe a significantly negative loading for the change of local economic indicators in loan loss provisioning regression.

H3: Local economic conditions are expected to strongly explain the loan loss provisioning of community banks.

Last but not at least, we reexamine the dynamic income smoothing process proposed by Liu and Ryan (2006). In the 1990s' economic boom, banks rimmed their income using loan loss provisions and created excessive reserves, effectively raising attention of regulators. In 1994, the General Accounting Office asserted that some banks created large portion of loan loss allowance that has no evidence of potentially supporting the possible loss. Later, SEC investigated the SunTrust bank and forced them to reduce their loan loss allowance by 100 million dollars. In 2001, SEC issued SAB 102 to regulate banks to adopt consistent methodology in estimating loan loss allowance. To this effect, Liu and Ryan (2006) propose that banks which smooth their income would obscure their behavior by using loan charge-offs and recoveries to achieve a stable loan loss allowance. In particular, Liu and Ryan (2006) hypothesize that banks which smooth their income would accelerate loan charge-offs during economic upturns and recover them in the next period; and banks with more recoveries would record more charge-offs at the same period to achieve stable loan loss allowances. Since most of the community banks are regulated by FFIEC, and community banks that are publicly traded are supervised by SEC, we hypothesize that consistent with commercial banks, community banks smooth loan loss allowance using charge-offs to avoid scrutiny from regulators.

H4: In community banks, banks accelerating loan charge-offs when they have excessive allowance and recovering them the next year and recording more loan charge-offs when they have more loan recoveries at the same year.

CHAPTER 4

SAMPLE SELECTION AND DATA

We use annual data of U.S. community banks from January 2001 to December 2016. We consider data after 2001 for two reasons. First, after 2001, there has been no regulatory changes except the International Financial Reporting Standards (IFRS) 9 Financial Instruments published in 2014 that replaces International Accounting Standards (IAS) 39 and becomes effective in 2017. Second, the data reporting for call reports changed significantly between 1976 and 2000.

Our sample is constructed using three sources of information. The first source of information is accounting information of banks. In U.S., all regulated banks are required to file the Consolidated Reports of Condition and Income (referred as call report), quarterly to provide financial and operation information to regulators. All the call report information is maintained by analysts at FDIC and publicly available. Therefore, call report data is the widely used data by regulators, investors and researchers. We obtain our desired accounting information by extracting information from banks' call reports[3], from Federal Reserve Bank of Chicago.

The second source of information is regional economic information. Federal Reserve Bank of Philadelphia releases state coincident indexes and state leading indexes constructed by Theodore Crone and Alan Clayton-Matthews[4]. The state coincident indexes are constructed using nonfarm payroll employment, average hours worked in manufacturing by production workers, the unemployment rate, and wage and salary disbursements deflated by the consumer price index (U.S. city average). The state coincident indexes are calculated monthly after Bureau of Labor Statistics publish the unemployment rate information for each state. The state leading indexes are modeled using the state coincident indexes and other factors which affect the long-term economy, and these indexes tend to predict the six-month changes in the state coincident indexes. Since we analyze annual earnings smoothing at community banks, to convert the monthly data to yearly data, we subtract the monthly value of state coincident indexes in January from that in December to estimate annual change in the coincident indexes yearly; and we take average of the state leading indexes for the last three months and last twelve months from a year end to reflect the regional economic

[3] The type of call reports used in our study is Consolidated Reports of Condition and Income for a Bank with Domestic Offices Only (FEIEC 041).

[4] See Crone, Theodore M., and Alan Clayton-Matthews. "Consistent Economic Indexes for the 50 States," Review of Economics and Statistics, 87 (2005), pp. 593-603.

change in next given year. Apart from the state-level economic indexes, we also include other economic variables used in previous studies. We derive the unemployment rate data from Bureau of Labor Statistics, and Case-Shiller index and GDP data are from Federal Reserve Economic Data maintained by Federal Reserve Bank of St. Louis.

The third source of information is the range of community banks. Although studies to date define community banks as those which focus on traditional lending and deposits gathering activities and mainly conduct business locally, it has been difficult for researchers to identify community banks in practice. Many previous researches adopted a billion dollars as a fixed cutoff in size to identify community banks. Another generally used restriction is a bank must not be a part of multi-bank holding company. In 2012, FDIC publishes a community banking study and it proposes a new way of defining community banks. It clearly points out the disadvantages of previous definition used to select the sample of community banks. First, the fixed size cutoff does not consider the inflation, growth of the industry as well as the economy. Second, the size itself cannot define the types of business banks are engaged in. Third, the size cutoff does not consider the geographic scope of business. Therefore, the new approach FDIC used to define community banks is only loosely related to size and includes more geographic and business activities information. Instead of using a fixed cutoff of size, they impose different size limit at different periods. Between 1985 and 2010, the size limit is 250 million dollars, and the limit is 1 billion dollars after 2010. They also gather other information such as loan to assets ratio and core deposits to assets ratio to control the types of business banks engage in. Other than that, restrictions such as maximum number of offices in metropolitan area and maximum states operating in are also considered due to the geographic scope of community banks. [5] A brief summary of methodology from FDIC community banking study (2012) is presented in Graph 4.1. By using this new approach, FDIC constructed the data set and made it available on their website for future study reference.

[5] See specific method in Appendix A, FDIC community banking study (2012).

Graph 4.1: Summary of FDIC community banking study (2012) methodology

Summary of FDIC Research Definition of Community Banking Organizations

Designate community banks at the level of the banking organization. All charters under designated holding companies are considered community banking charters.

Exclude:

Any organization with:
- No loans or no core deposits
- Foreign Assets ≥ 10% of total assets
- More than 50% of assets in certain specialty banks, including:
  - credit card specialists
  - consumer nonbank banks[1]
  - industrial loan companies
  - trust companies
  - bankers' banks

[1] Consumer nonbank banks are financial institutions with limited charters that can make commercial loans or take deposits, but not both.

Include:

All remaining banking organizations with:
- Total assets < indexed size threshold[2]
- Total assets ≥ indexed size threshold, where:
  - Loan to assets > 33%
  - Core deposits to assets > 50%
  - More than 1 office but no more than the indexed maximum number of offices.[3]
  - Number of large MSAs with offices ≤ 2
  - Number of states with offices ≤ 3
  - No single office with deposits > indexed maximum branch deposit size.[4]

[2] Asset size threshold indexed to equal $250 million in 1985 and $1 billion in 2010.
[3] Maximum number of offices indexed to equal 40 in 1985 and 75 in 2010.
[4] Maximum branch deposit size indexed to equal $1.25 billion in 1985 and $5 billion in 2010.

Source: FDIC.

Source: FDIC community banking study (2012)

Gathering data from all the sources mentioned above, we construct our variables. Definitions and calculations of variables used are provided in Table 4.1.

Table 4.1: Definitions of variables

Variable Name	Variable Definition	Calculation
PLLN_A	Percentage of Loan loss provisions for the year over lagged total assets;	RIAD4230/ lagged (RCON2170);
X	Earnings after tax plus loan loss provisions over lagged total assets;	(RIAD4340+RIAD4230)/ lagged (RCON2170);
ASSET	Total assets in thousands of dollars;	RCON2170;
SIZE	Logged lagged total assets in thousands of dollars;	Logged (lagged (RCON2170));
DLOAN	The change in total outstanding loans scaled by lagged total assets;	(RCON2122-lagged (RCON2122))/ lagged (RCON2170);

LAG1_NPL	Non-performing loans at the end of last year;	Lagged (RCON items including past due 90 days or more and still accruing and nonaccrual loans, leases and other assets)/ lagged (RCON2170);
NAL	Nonaccrual loans, leases and other assets;	RCON items including all the nonaccrual loans, leases and other assets /lagged (RCON2170);
INLOAN	Loans to individuals for household, family, and other personal expenditures scaled by lagged total assets;	(RCONB538+RCONB539+RCON2011)/ lagged (RCON2170);
COMLOAN	Commercial and industrial loans scaled by lagged total assets.	RCON1766/ lagged (RCON2170).
DNPA	The change in the nonperforming assets scaled by lagged total assets;	Yearly change in RCON items including past due 90 days or more and still accruing and nonaccrual loans, leases and other assets/lagged (RCON2170);
LEAD_DNPA	One year ahead DNPA;	
LAG1_DNPA	First lag of DNPA;	
LAG2_DNPA	Second lag of DNPA;	
LAG3_DNPA	Third lag of DNPA;	
CAP_EA	Equity to asset ratio;	RCON3210/RCON2170;
LAG1_ CAP_EA	Equity to asset ratio at the end of last year;	
ALL	Allowance at the end of the year scaled by lagged total assets;	RIAD3123/ lagged (RCON2170);
LAG1_ALL	Allowance at the end of last year scaled by lagged total assets;	RIADB522/ lagged (RCON2170);
REC	Recoveries on loans and leases scaled by lagged total assets;	RIAD4605/ lagged (RCON2170);
NLCO	Net loan charge-offs on loans and leases scaled by lagged total assets;	(RIAD4635-RIAD4605)/ lagged (RCON2170);
GLCO	Gross loan charge-offs on loans and leases;	RIAD4635/ lagged (RCON2170);
LAG1_GLCO	First lag of GLCO;	
PERIOD1	Dummy variable equals to 1 if it is year before 2008;	
PERIOD2	Dummy variable equals to 1 if it is year between 2008 to 2010;	
PERIOD3	Dummy variable equals to 1 if it is year after 2010;	

BHC	Dummy variable equals to 1 if the community bank is part of bank holding company;	
X_BHC	Interaction between variable X and BHC;	
DGDP	The yearly change in GDP;	
LEAD_3M	Last three months average at the end of a year of the state leading index from Federal Reserve Bank of Philadelphia scaled by 100;	
LEAD_12M	Last twelve months average at the end of a year of the state leading index from Federal Reserve Bank of Philadelphia scaled by 100;	
BHC_LEAD_3M	Interaction between variable LEAD_3M and BHC;	
DCOIN	The yearly change in the state coincident index from Federal Reserve Bank of Philadelphia scaled by 100;	
CSRET	The yearly return on Case-Shiller U.S. National Home Price Index from Federal Reserve Economic Data;	
DUNRATE	The yearly change in the unemployment rate from Bureau of Labor Statistics;	
HOM_PER	The percentage of homogeneous loans scaled by lagged total asset;	
X_HOM	The interaction between variable X and HOM_PER (the percentage of homogeneous loans scaled by lagged total asset);	
HIGH_ROA	dummy variable equals to 1 if a bank's ROA exceeds the median ROA of all banks of the year;	
X_ROA	The interaction between variable X and HIGH_ROA (dummy variable equals to 1 if a bank's ROA exceeds the median ROA of all banks of the year).	

All the codes used to construct the accounting variables are from Consolidated Reports of Condition and Income for A Bank with Domestic Offices Only—FFIEC 041 200103 form.

We include almost all the accounting variables used in previous loan loss provisioning models. Following Laeven and Majnoni (2003), accounting variables are scaled by lagged asset to avoid potential endogeneity problem. DCOIN (change in coincident indexes) is a variable represents the current economic change. Since the coincident index from Federal Reserve Bank of Philadelphia releases monthly, we convert the monthly data to yearly data by subtracting the index at the beginning of the year from the index at the end of the year. LEAD_3M (lead index, 3 months average) and LEAD_12M (lead index, 12 months average) are both economic lead indicators. As explained above, the lead index from Federal Reserve Bank of Philadelphia estimates the change in coincident index for next six months. We take average of the lead index at last three months and last twelve months respectively to represent the future economic changes. In addition, we include some dummy variables. To control for financial crisis, we use dummies PERIOD 1(year 2001 to 2007) to PERIOD 3 (year after 2010). To see the effect of a community bank being part of a bank holding company, we include BHC (dummy for community banks that are part of bank holding companies).

CHAPTER 5

METHODOLOGY

Beatty and Liao (2014) summarize the important loan loss provisioning models from the existing literature. Since there is no consensus an optimal loan loss provisioning model, we select five models based on models proposed in the new capital regime (post-BASEL). We denote these five models as Model 1-5 and they are respectively from: Laeven and Majnoni (2003), Liu and Ryan (2006), Kanagaretnam et al. (2010), Bushman and Williams (2012), and Beck and Narayanamoorthy (2013). Following Beatty and Liao (2014), we select these five models and further test our hypotheses 1-3. Model 1-5 are as follows:

$$PLLN\_A = a_0 + a_1X + a_2DLOAN + a_3DGDP + a_4PERIOD1 + a_5PERIOD3 + \varepsilon \quad (5.1)$$

$$PLLN\_A = a_0 + a_1X + a_2HIGH\_ROA + a_3X\_HOM + a_4X\_ROA + a_5DNPA + a_6CAP\_EA + a_7PERIOD1 + a_8PERIOD3 + \varepsilon \quad (5.2)$$

$$PLLN\_A = a_0 + a_1X + a_2LAG1\_ALL + a_3LAG1\_NPL + a_4NLCO + a_5DNPA + a_6DLOAN + a_7PERIOD1 + a_8PERIOD3 + \varepsilon \quad (5.3)$$

$$PLLN\_A = a_0 + a_1DNPA + a_2LEAD\_DNPA + a_3LAG1\_DNPA + a_4LAG2\_DNPA + a_5DGDP + a_6SIZE + a_7LAG1\_CAP\_EA + a_8PERIOD1 + a_9PERIOD3 + \varepsilon \quad (5.4)$$

$$PLLN\_A = a_0 + a_1X + a_2LAG1\_ALL + a_3DNPA + a_4SIZE + a_5GLCO + a_6INLOAN + a_7COMLOAN + a_8CSRET + a_9PERIOD1 + a_{10}PERIOD3 + \varepsilon \quad (5.5)$$

The most commonly used control variable in these five models is the change in the non-performing loans. The change in the non-performing loans (DNPA) is expected to predict the next year's nonperforming loans. Collins et al. (1995) use the change in the non-performing loans representing the default risk of loan portfolios and find the coefficients on DNPA load with a significantly positive sign. Consistent with Collins et al. (1995), Ahmed et al. (1999) and Liu and Ryan (2006) also use the same variable in their models and report the coefficients are significantly positive. Bushman and Williams (2012) use the change in the non-performing loans in different time periods - future, current and past two years in their model and find that all these variables load with significantly positive coefficients.

Laeven and Majnoni (2003) include the change in the outstanding loans (DLOAN) in loan loss provisioning regression to control for bank risk. They argue the more rapidly the loans grow, the more risk the loans portfolio will have due to less supervision. However, contrary to their expectation, Laven and Majnoni find the loan growth rate is significantly negatively related to loan loss provisions. Their results show that banks are less prudent estimating loan loss provisions when it comes to rapidly expanded loans portfolios. Kanagaretnam et al. (2010) also include DLOAN in their model, and they consider the variable can be related to loan loss provisions in either direction because of the uncertainty of the nature of loans increased. Nevertheless, the coefficient on DLOAN is not significant in their model.

Kanagaretnam et al. (2010) and Beck and Narayanamoorthy (2013) use the last year-end loan loss allowance (LAG1_ALL) in their models, Kanagaretnam et al. (2010) points out the more the last year-end loan loss allowance, the lesser the required loan loss provisions. Both studies find the relationship between LAG1_ALL and loan loss provisions is significantly negative. Similarly, Kanagaretnam et al. (2010) add the last year-end non-performing loans in their model, because the higher the level of last year-end non-performing loans (LAG1_NPL), the higher the level of loan loss provisions. But their result does not show any significance of LAG1_NPL.

Kanagaretnam et al. (2010) and Beck and Narayanamoorthy (2013) use net loan charge-offs (NLCO) and gross loan charge-offs (GLCO) respectively, and coefficients on these two variables are all significantly positive. Beaver and Engel (1996) argue current loan charge-offs can provide information of future charge-offs, therefore provide information of future non-performing loans which affect loan loss provisions.

Liu and Ryan (2006) and Bushman and Williams (2012) use tier 1 capital ratio and its lag to control for the regulatory purposes and they find no significance of the variable in Liu and Ryan (2006)'s model and significantly negative in Bushman and Williams (2012)'s. The reason for the variable not being significant in Liu and Ryan (2006)'s model is that they only focus on the boom period, therefore it is highly likely banks are all well capitalized. Capital ratio is widely used in loan loss provisioning models. At pre-BASEL period, loan loss allowance can be counted as tier 1 capital, as a result, an increase in loan loss provisions leads to an increase in tier 1 capital ratio. At post-BASEL period, loan loss allowance is no longer a part of tier 1 capital, therefore, tier 1 capital ratio decreases when loan loss provisions increase. Moyer (1990) provides evidence that during pre-BASEL period, banks manipulate the timing of provisions due to capital requirement.

Beatty (1995) asserts loan charge-offs, loan loss provisions, and the decision to issue securities are jointly determined, probably because all three are used to meet capital requirement. And banks trade accruals for meeting the capital requirement. Collins et al. (1995) on the contrary find a positive relation between loan loss provisions and capital ratio. They explain this inconsistent result is possibly related to model specification. Compared with studies at pre-BASEL period, there are less studies related to capital ratio at post-BASEL period. Kim and Kross (1998) and Ahmed et al. (1999) research post-BASEL period, and they find less incentives for banks to indulge in capital management.

Size control is used in Bushman and Williams (2012) and Beck and Narayanamoorthy (2013) to control for potential size effect on loan loss provisions. Bushman and Williams (2012) find the coefficient on size significantly positive while Beck and Narayanamoorthy (2013) do not find it significant. Watts and Zimmerman (1986) propose a positive relation between loan loss provisions and size because of the political cost. A larger bank can attract more attention from the regulators and therefore allocates more in loan loss provisions. Moyer (1990) includes the natural log of earnings as a size measure and finds size is significantly negatively associated with loan loss provisions, which is contrary to their expectation. Kim and Kross (1998) apply size control and they find it significantly positive.

Kanagaretnam et al. (2010) include six loan categories in their model to control for any additional effect that loan composition might bring. As explained by Kanagaretnam et al. (2010), riskier loans such as commercial loans can lead to more loan loss provisions. Their results show that commercial loans have significantly positive effect on loan loss provisions, and consumer loans have significantly negative effect on loan loss provisions. Beck and Narayanamoorthy (2013) control only these two loan categories in their study, and the results show a significant coefficient only for commercial loans.

Except variables representing accounting information, loan loss provisioning models have also used many macroeconomic variables. Laeven and Majnoni (2003) and Bushman and Williams (2012) incorporate the change in the GDP (DGDP) in their models to control for the overall economy. Laeven and Majnoni (2003) discover that on average banks record less provisions when economy grows, but DGDP loads with an insignificant coefficient in the model of Bushman and Williams (2012). Beck and Narayanamoorthy (2013) include change in the unemployment rate

(DUNRATE) and return on Case-Shiller index (CSRET) as macroeconomic variables, and both these variables load with statistically significant coefficients.

We keep almost all the variables used in Laeven and Majnoni (2003), Liu and Ryan (2006), Kanagaretnam et al. (2010), Bushman and Williams (2012), and Beck and Narayanamoorthy (2013). Whereas, models are tailored in our specific case. First, time indicators are added to control for the financial crisis in 2008. Second, Laeven and Majnoni (2003) claim scaling variables by last year-end asset can avoid potential endogeneity problem, following Laeven and Majnoni (2003), we scale variables using last year-end asset. Third, all the models use bank-specific effect. Fourth, some variables used in literature are dropped because of collinearity problem. For instance, DUNRATE is dropped because it is highly correlated with CSRET in our sample. After these modifications, we derive five loan loss provisioning models to test our hypotheses 1-3.

To examine hypothesis 1 that the community banks use loan loss provisions for earning management, we use our core Models 1-5. We expect a positive and significant relation between percentage of loan loss provisions for the year over lagged total assets (PLLN_A) and our key dependent variable, earnings after tax plus loan loss provisions over lagged total assets (X) in all five models which indicates community banks estimate more loan loss provisions when they have more earnings.

We add X_BHC in Models 1-5 to test hypothesis 2. BHC is a dummy variable takes value of 1 if a community bank is part of a bank holding company. X_BHC is the interaction between BHC and X, which enable us to capture the heterogeneity in earning management between community banks which are part of bank holding companies and standalone community banks. A community bank which is part of a bank holding company can be controlled by another bank holding company or itself be the top parent bank holding company. We also tend to include BHC to control for any direct effect from being a bank holding company, however, we could not include BHC since it is highly correlated with X_BHC. The coefficient on X_BHC is expected to be significant and negative, since being part of a bank holding company can diversify risks.

We add LEAD_3M in Models 1-5 to test hypothesis 3. LEAD_3M is a 3-months averages of state economic lead indicator. We also have 12-months averages, LEAD_12M, while LEAD_3M and LEAD_12M are highly correlated. We choose LEAD_3M as the variable represents future local economic change information banks have. In addition, other macroeconomic variables are dropped in Models 1-5 due to collinearity problem. We expect the coefficient on LEAD_3M to be significant and negative. This would indicate that local economic variations affect loan loss provisioning in community banks.

We use dynamic income smoothing models proposed by Liu and Ryan (2006) to test our hypothesis 4. Liu and Ryan (2006) treat charge-offs discretionary and they propose that in order to keep loan loss allowance relatively stable to avoid examination by regulators, banks use loan charge-offs and recoveries to achieve a dynamic income smoothing process. The dynamic income smoothing models tested in our study are as follows:

$REC = a_0 + a_1 LAG1\_GLCO + a_2 BHC + a_3 BHC\_LGLCO + a_4 LAG1\_CAP\_EA + a_5 DNPA + a_6 LAG1\_DNPA + a_7 LAG2\_DNPA + a_8 LAG3\_DNPA + a_9 SIZE + a_{10} PERIOD1 + a_{11} PERIOD3 + a_{12} LOCALINDICATOR + \varepsilon$ ....(5.6)

$GLCO = a_0 + a_1 REC + a_2 BHC + a_3 BHC\_REC + a_4 CAP\_EA + a_5 PLLN\_A + a_6 LAG1\_ALL + a_7 DNPA + a_8 SIZE + a_9 PERIOD1 + a_{10} PERIOD3 + a_{11} LOCALINDICATOR + \varepsilon$ ....(5.7)

Compared with models developed by Liu and Ryan (2006), Model 6-7 include a BHC dummy, an interaction between BHC and lag variable of gloss loan charge-offs, time indicators and local economic indicators. BHC and an interaction between BHC and recoveries on loans and leases scaled by lagged total assets (REC) denoted as BHC_REC are used to capture any possible effects in dynamic income smoothing from being part of a bank holding company. Time indicators capture effects from financial crisis, and local economic indicators capture local economic information in dynamic income smoothing. The coefficient on lagged gross loan charge-offs (LAG1_GLCO) of Model 6 is expected to be significantly positive, which shows the higher the previous year's charge-offs, the higher this year's recoveries. In addition, we expect the coefficient on REC of Model 7 to be significant and positive. This suggests the more recoveries this year, the more charge-offs would be recorded at the same year.

CHAPTER 6

EMPIRICAL RESULTS

6.1 Descriptive Statistics

Table 6.1 reports descriptive statistics of our sample after winsorization at 1% level at both tails. We have 8,485 individual banks in our sample and 74,630 bank-year observations. We note, on average, community banks allocate 0.35% of their last year-end assets as their loan loss provisions, however, they range from minimum of -0.50% to maximum of 6.02% of the last year-end assets. A phenomenon noteworthy is that some banks record negative loan loss provisions. Banks record negative loan loss provisions when newly estimated loan loss allowance is less than the balance of loan loss allowance account (Stephen, 2013). The average asset of community banks is 0.29 billion, and maximum 4.1 billion. Different from previous community banking study, large banks as large as 4.1 billion are also included in our study. Whereas, asset at 75 percentiles is 0.32 billion, which infers that majority of banks in our sample are small community banks. We can also notice most of the community banks in our sample have a flat rate of loan loss allowance, generally 1% of the last year-end asset. The BHC dummy's mean is 0.82, which indicates 82% of community banks in our sample are part of bank holding companies, and 18% of community banks in our sample are standalone banks not related to bank holding companies.

Table 6.1: Descriptive Statistics

Variable	N	Mean	S.D.	Min	0.25	Mdn	0.75	Max
PLLN_A	74630	0.35	0.59	-0.50	0.06	0.17	0.17	6.02
ASSET	74630	290000.	410000	12826.	79095.	150000.	320000.	4100000.
X	74630	0.01	0.01	-0.03	0.01	0.01	0.02	0.04
DNPA	74630	0.00	0.01	-0.05	0.00	0.00	0.00	0.09
ALL	74630	0.01	0.01	0.00	0.01	0.01	0.01	0.04
NLCO	74630	0.00	0.01	0.00	0.00	0.00	0.00	0.05
GLCO	74630	0.00	0.01	0.00	0.00	0.00	0.00	0.05
DLOAN	74630	0.04	0.09	-0.19	-0.01	0.03	0.07	0.54
SIZE	74630	11.95	1.03	9.44	11.23	11.90	12.63	15.11
CAP_EA	74630	0.10	0.03	0.02	0.09	0.10	0.12	0.23
REC	74630	0.00	0.00	0.00	0.00	0.00	0.00	0.01
NAL	74630	0.01	0.01	0.00	0.00	0.01	0.01	0.13
INLOAN	74630	0.05	0.05	0.00	0.01	0.03	0.06	0.28
COMLOA	74630	0.10	0.07	0.00	0.05	0.08	0.12	0.41
DGDP	74630	2.07	1.45	-2.80	1.70	2.40	2.70	4.40

LEAD_3	74630	0.01	0.01	-0.06	0.01	0.01	0.02	0.05
LEAD_12	74630	0.01	0.01	-0.05	0.01	0.01	0.02	0.05
DCOIN	74630	0.04	0.04	-0.17	0.02	0.04	0.06	0.17
DUNRAT	74630	0.00	0.01	-0.01	-0.01	0.00	0.00	0.03
CSRET	74630	0.04	0.07	-0.13	-0.03	0.06	0.10	0.14
BHC	74630	0.82	0.39	0.00	1.00	1.00	1.00	1.00

PLLN_A: Percentage of Loan loss provisions for the year over lagged total assets. ASSET: Total assets in thousands of dollars; X: Earnings after tax plus loan loss provisions over lagged total assets. DNPA: The change in the nonperforming assets scaled by lagged total assets; ALL: Allowance at the end of the year scaled by lagged total assets; NLCO: Net loan charge-offs on loans and leases; GLCO: Gross loan charge-offs on loans and leases; DLOAN: The change in total outstanding loans scaled by lagged total assets. ASSET: Total assets in thousands of dollars; SIZE: Logged lagged total assets in thousands of dollars; CAP_EA: Equity to asset ratio; REC: Recoveries on loans and leases; NAL: Nonaccrual loans, leases and other assets; INLOAN: Loans to individuals for household, family, and other personal expenditures scaled by lagged total assets; COMLOAN: Commercial and industrial loans scaled by lagged total assets; DGDP: The change in GDP. LEAD_3M: Last three months average at the end of a year of the state leading index from Federal Reserve Bank of Philadelphia; LEAD_12M: Last twelve months average at the end of a year of the state leading index from Federal Reserve Bank of Philadelphia scaled by 100; DCOIN: The yearly change in the state coincident index from Federal Reserve Bank of Philadelphia scaled by 100; DUNRATE: The yearly change in the unemployment rate from Bureau of Labor Statistics; CSRET: The yearly return on Case-Shiller U.S. National Home Price Index from Federal Reserve Economic Data; BHC: Dummy variable equals to 1 if the community bank is part of bank holding company.

Table 6.2 provides the pairwise correlation coefficients of regression variables. Accounting variables and economic variables are measured separately. As we can see from Panel A of Table 6.2, the net loan charge-offs and gross loan charge-offs have the strongest correlation with loan loss provisions. It is reasonable since charge-offs are directly related to loan loss provisions. Panel B shows the correlations of economic variables, the state-level economic indicators are highly correlated.

Table 6.2: Correlations of accounting variables and economic variables

Panel A: Correlations of accounting variables

	PLLN_A	X	DNPA	ALL	NLCO	GLCO
PLLN_A	1					
X	-0.07*	1				
DNPA	0.31*	0.06*	1			
ALL	0.56*	-0.03*	0.14*	1		
NLCO	0.87*	-0.16*	0.11*	0.47*	1	
GLCO	0.85*	-0.16*	0.09*	0.50*	0.98*	1
DLOAN	-0.13*	0.26*	0.10*	-0.01*	-0.28*	-0.28*
SIZE	0.07*	0.07*	0.03*	0.05*	0.05*	0.04*
CAP_EA	-0.19*	0.14*	-0.06*	-0.09*	-0.16*	-0.15*
REC	0.09*	-0.05*	-0.12*	0.30*	0.16*	0.32*
NAL	0.60*	-0.28*	0.39*	0.54*	0.60*	0.60*
INLOAN	-0.03*	0.21*	0.02*	-0.08*	-0.05*	-0.03*
COMLOAN	0.10*	0.18*	0.06*	0.19*	0.04*	0.04*

	DLOAN	SIZE	CAP_EA	REC	NAL	INLOAN	COMLOAN
DLOAN	1						
SIZE	0.07*	1					
CAP_EA	-0.05*	-0.12*	1				
REC	-0.11*	-0.05*	0.03*	1			
NAL	-0.24*	0.09*	-0.13*	0.15*	1		
INLOAN	0.11*	-0.29*	-0.01	0.11*	-0.18*	1	
COMLOAN	0.35*	0.04*	-0.13*	0.03*	-0.02*	0.03*	1

Panel B: Correlations of economic variables

	DGDP	LEAD_3M	LEAD_12M	DCOIN	DUNRATE	CSRET
DGDP	1					
LEAD_3M	0.34*	1				
LEAD_12M	0.30*	0.83*	1			
DCOIN	0.52*	0.78*	0.69*	1		
DUNRATE	-0.78*	-0.59*	-0.52*	-0.76*	1	
CSRET	0.67*	0.20*	0.27*	0.31*	-0.53*	1

PLLN_A: Percentage of Loan loss provisions for the year over lagged total assets. X: Earnings after tax plus loan loss provisions over lagged total assets. DNPA: The change in the nonperforming assets scaled by lagged total assets; ALL: Allowance at the end of the year scaled by lagged total assets; NLCO: Net loan charge-offs on loans and leases; GLCO: Gross loan charge-offs on loans and leases; DLOAN: The change in total outstanding loans scaled by lagged total assets; SIZE: Logged lagged total assets in thousands of dollars; CAP_EA: Equity to asset ratio; REC: Recoveries on loans and leases; NAL: Nonaccrual loans, leases and other assets; INLOAN: Loans to individuals for household, family, and other personal expenditures scaled by lagged total assets; COMLOAN: Commercial and industrial loans scaled by lagged total assets; DGDP: The change in GDP; LEAD_3M: Last three months average at the end of a year of the state leading index from Federal Reserve Bank of Philadelphia; LEAD_12M: Last twelve months average at the end of a year of the state leading index from Federal Reserve Bank of Philadelphia scaled by 100; DCOIN: The yearly change in the state coincident index from Federal Reserve Bank of Philadelphia scaled by 100; DUNRATE: The yearly change in the unemployment rate from Bureau of Labor Statistics; CSRET: The yearly return on Case-Shiller U.S. National Home Price Index from Federal Reserve Economic Data.

* Significance at a 1% level.

6.2 Regresion Results

Table 6.3 reports results based on all five loan loss provisioning models we define in section 4. A positive and significant coefficient on X represents the existence of earning management, more specifically, the evidence of use of loan loss provisions to smooth earnings. All the models tested show the earning management behavior of community banks. In column 1, we use Laeven and Majnoni (2003) model, and we find that our key test variable X loads with a positive and significant (at 1% level) coefficient. In column 2, we use Liu and Ryan (2006) model and find the coefficient of our test variable X loads with a positive and significant coefficient (at 1% level). In column 3, we run Kanagaretnam et al. (2010)'s model, and we discover X loads with positive and significant (at 1% level) coefficient. In column 4, we regress Bushman and Williams (2012)'s model, and we find our test variable X loads with a positive and significant coefficient (at 1% level). In column 5, we regress Beck and Narayanamoorthy (2013)' model, and we find X loads with a significant (at 1% level) and positive coefficient. Overall, result from table 6.3 provides strong evidence that community banks use loan loss provisions to smooth income, supporting our hypothesis 1.

Table 6.3: Loan loss provisions regressions from literature

VARIABLES	(Laeven and Majnoni, 2003) PLLN_A	(Liu and Ryan, 2006) PLLN_A	(Kanagaretnam etal., 2010) PLLN_A	(Bushman and Williams, 2012) PLLN_A	(Beck and Narayanmoorthy, 2013) PLLN_A
X	3.976***	16.851***	3.714***	2.537***	4.054***
	(0.902)	(1.647)	(0.433)	(0.938)	(0.439)
HIGH_ROA		-0.534***			
		(0.013)			
X_HOM		14.401***			
		(2.302)			
X_ROA		-			
		(1.589)			
LAG1_ALL			-27.803***		-30.355***
			(1.237)		(1.295)
LAG1_NPL			0.178		
			(0.246)		
NLCO			102.161***		
			(0.653)		
DNPA		9.349***	7.584***	12.127**	8.317***

		(0.377)	(0.268)	(0.458)	(0.239)
DLOAN	-		0.073**		
	(0.046)		(0.029)		
PERIOD1	-	-0.291***	-0.112***	-	-0.134***
	(0.009)	(0.007)	(0.004)	(0.010)	(0.005)
PERIOD3	-	-0.257***	-0.091***	-	-0.107***
	(0.009)	(0.007)	(0.004)	(0.008)	(0.005)
DGDP	-			0.002	
	(0.002)			(0.002)	
CAP_EA		-5.730***			
		(0.229)			
LEAD_DNPA				-	
				(0.373)	
LAG1_DNPA				14.916**	
				(0.412)	
LAG2_DNPA				10.989**	
				(0.318)	
SIZE				0.020	0.009
				(0.016)	(0.007)
LAG1_CAP_EA				-0.210	
				(0.221)	
GLCO					99.322***
					(0.655)
INLOAN					0.214***
					(0.082)
COMLOAN					0.419***
					(0.044)
CSRET					0.044**
					(0.018)
Constant	0.756***	1.474***	0.344***	0.306	0.175*
	(0.013)	(0.029)	(0.014)	(0.197)	(0.090)
Observations	74,630	74,630	66,145	50,772	74,630
R-squared	0.190	0.361	0.803	0.322	0.784
Number of banks	8,485	8,485	7,962	6,888	8,485
R2 within	0.190	0.361	0.803	0.322	0.784
R2 overall	0.145	0.329	0.804	0.278	0.786
R2 between	0.107	0.331	0.848	0.261	0.821
F-stat	725.7	922.1	6039	502.8	4340
Prob > F	0	0	0	0	0

PLLN_A: Percentage of Loan loss provisions for the year over lagged total assets; X: Earnings after tax plus loan loss provisions over lagged total assets. HIGH_ROA: dummy variable equals to 1 if a bank's ROA exceeds the median ROA of all banks of the year. X_HOM: The interaction between variable X and HOM_PER (the percentage of homogeneous loans scaled by lagged total asset). X_ROA: The interaction between variable X and HIGH_ROA (dummy variable equals to 1 if a bank's ROA exceeds the median ROA of all banks of the year). DLOAN: The change in total outstanding loans scaled by lagged total assets; PERIOD1: Dummy variable equals to 1 if it is year before 2008; PERIOD3: Dummy variable equals to 1 if it is year after 2010; DGDP: The change in GDP; DNPA: The change in the nonperforming assets scaled by lagged total assets; CAP_EA: Equity to asset ratio; LAG1_ALL: Allowance at the end of last year scaled by lagged total assets; LAG1_NPL: Non-performing loans at the end of last year; NLCO: Net loan charge-offs on loans and leases; LEAD_DNPA: One year ahead DNPA; LAG1_DNPA: First lag of DNPA; LAG2_DNPA: Second lag of DNPA; SIZE: Logged lagged total assets in thousands of dollars; LAG1_CAP_EA: Equity to asset ratio at the end of the year; GLCO: Gross loan charge-offs on loans and leases; INLOAN: Loans to individuals for household, family, and other personal expenditures scaled by lagged total assets; COMLOAN: Commercial and industrial loans scaled by lagged total assets; CSRET: The yearly return on Case-Shiller U.S. National Home Price Index from Federal Reserve Economic Data.

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

As for the control variables of these five models, we find different result from Liu and Ryan (2006) on coefficient of HIGH_ROA (a dummy takes 1 when a bank has above-median ROA) and X_ROA (an interaction between X and HIGH_ROA). Liu and Ryan (2006) propose a positive coefficient of X_ROA by arguing the more profitable banks tend to have more aggressive earning management during boom. However, our result finds the opposite result. The reason might be instead of studying the banks during boom, we include both boom and bust periods, and use time indicators in our regressions. In addition, the coefficient of one year ahead DNPA (LEAD_DNPA) is also find at an opposite direction, whereas the coefficients on lag one of DNPA (LAG1_DNPA) and lag two of DNPA (LAG2_DNPA) are as expected significantly positive. This result may indicate that community banks increase their loan loss provisions mainly in response to past nonperforming loans information.

The coefficients of other control variables are consistent with the literature. The result regarding homogenous loans is consistent with Liu and Ryan (2006)'s. We find a positive and significant coefficient of homogenous loans. The coefficient of last year-end loan loss allowance scaled by lagged assets (LAG1_ALL) is significant and negative, representing the more loan loss allowance at last year end, the less loan loss provisions needed for this year. Consistent with Kanagaretnam et al. (2010), the coefficient of last year-end nonperforming loans scaled by total assets (LAG1_NPL) does not show any significance. NLCO and GLCO have relatively strong effects on loan loss provisions which are consistent with Knagaretnam et al. (2010) and Narayanamoorthy (2013). All the models show significantly positive coefficients on DNPA. The coefficients of DLOAN have inconsistent result in the literature. Laeven and Majnoni (2003) find a significantly negative coefficient on DLOAN, whereas, Kanagaretnam et al. (2010) do not find a significant result. We find consistent result with Laeven and Majnoni (2003), but the coefficient is significantly positive in the model of Kanagaretnam et al. (2010). Consistent with the literature, DGDP is significantly negative in Laeven and Majnoni (2003)'s model and not significant in Bushman and Williams. Capital ratios represent a significantly negative association with loan loss provisions. Size effect on loan loss provisions is not significant in our result. Loan compositions are significant in our result, and commercial loans are associated with more loan loss provisions compared to individual loans. Beck and Narayanamoorthy (2013) find similar result of coefficient on commercial loans, but they do not find any significant result for individual loans. The coefficients of time indicators are as expected significantly negative, which show that before and after financial crisis, the loan loss provisions are less on average compared with the financial crisis period.

Table 6.4 reports the result of loan loss provisions and the effect of being part of a bank holding company. Except in column 2, we find insignificant results on X_BHC in other four columns. In column 2, we find X_BHC loads with a negative and significant (at 10% level) coefficient. Results from other four columns do not provide evidence that supports our hypothesis 2 that community banks that are part of bank holding companies are less aggressive in income smoothing. Additionally, X loads with positive and significant coefficients in all five models, which again provides strong evidence of income smoothing using loan loss provisions. Results for other control variables are consistent with the results in Table 6.3.

Table 6.4: Loan loss provisions and the effect of bank holding company

	(Laeven and Majnoni, 2003)	(Liu and Ryan, 2006)	(Kanagaretnam etal., 2010)	(Bushman and Williams, 2012)	(Beck and Narayanmoorthy, 2013)

VARIABLES	PLLN_A	PLLN_A	PLLN_A	PLLN_A	PLLN_A
X	3.796**	18.738***	4.448***	4.117**	4.692***
	(1.491)	(1.950)	(0.745)	(1.738)	(0.739)
X_BHC	0.222	-2.358*	-0.886	-1.857	-0.790
	(1.454)	(1.372)	(0.736)	(1.751)	(0.713)
HIGH_ROA		-0.536***			
		(0.013)			
X_HOM		14.221***			
		(2.283)			
X_ROA		-11.328***			
		(1.599)			
LAG1_ALL			-27.805***		-30.354***
			(1.237)		(1.296)
LAG1_NPL			0.178		
			(0.246)		
NLCO			102.161***		
			(0.653)		
DNPA		9.358***	7.585***	12.132**	8.317***
		(0.377)	(0.268)	(0.458)	(0.239)
DLOAN	-		0.074***		
	(0.046)		(0.028)		
PERIOD1	-	-0.292***	-0.112***	-	-0.134***
	(0.009)	(0.007)	(0.004)	(0.010)	(0.005)
PERIOD3	-	-0.257***	-0.091***	-	-0.107***
	(0.009)	(0.007)	(0.004)	(0.008)	(0.005)
DGDP	-			0.002	
	(0.002)			(0.002)	
CAP_EA		-5.742***			
		(0.230)			
LEAD_DNPA				-	
				(0.373)	
LAG1_DNPA				14.917**	
				(0.412)	
LAG2_DNPA				10.990**	
				(0.318)	
SIZE				0.020	0.010
				(0.016)	(0.007)
LAG1_CAP_EA				-0.216	
				(0.221)	
GLCO					99.319***
					(0.655)
INLOAN					0.214***
					(0.082)
COMLOAN					0.421***

					(0.044)
CSRET					0.043**
					(0.018)
Constant	0.756***	1.477***	0.345***	0.302	0.169*
	(0.013)	(0.029)	(0.014)	(0.197)	(0.089)
Observations	74,630	74,630	66,145	50,772	74,630
R-squared	0.190	0.361	0.803	0.322	0.784
Number of banks	8,485	8,485	7,962	6,888	8,485
R2 within	0.190	0.361	0.803	0.322	0.784
R2 overall	0.145	0.330	0.804	0.278	0.786
R2 between	0.108	0.331	0.848	0.260	0.821
F-stat	604.7	820.4	5374	457.3	3952
Prob > F	0	0	0	0	0

PLLN_A: Percentage of Loan loss provisions for the year over lagged total assets; X: Earnings after tax plus loan loss provisions over lagged total assets. HIGH_ROA: dummy variable equals to 1 if a bank's ROA exceeds the median ROA of all banks of the year. X_HOM: The interaction between variable X and HOM_PER (the percentage of homogeneous loans scaled by lagged total asset). X_ROA: The interaction between variable X and HIGH_ROA (dummy variable equals to 1 if a bank's ROA exceeds the median ROA of all banks of the year). DLOAN: The change in total outstanding loans scaled by lagged total assets; PERIOD1: Dummy variable equals to 1 if it is year before 2008; PERIOD3: Dummy variable equals to 1 if it is year after 2010; DGDP: The change in GDP; DNPA: The change in the nonperforming assets scaled by lagged total assets; CAP_EA: Equity to asset ratio; LAG1_ALL: Allowance at the end of last year scaled by lagged total assets; LAG1_NPL: Non-performing loans at the end of last year; NLCO: Net loan charge-offs on loans and leases; LEAD_DNPA: One year ahead DNPA; LAG1_DNPA: First lag of DNPA; LAG2_DNPA: Second lag of DNPA; SIZE: Logged lagged total assets in thousands of dollars; LAG1_CAP_EA: Equity to asset ratio at the end of the year; GLCO: Gross loan charge-offs on loans and leases; INLOAN: Loans to individuals for household, family, and other personal expenditures scaled by lagged total assets; COMLOAN: Commercial and industrial loans scaled by lagged total assets; CSRET: The yearly return on Case-Shiller U.S. National Home Price Index from Federal Reserve Economic Data; BHC: Dummy variable equals to 1 if the community bank is part of bank holding company; X_BHC: Interaction between variable X and BHC.

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6.5 we further test loan loss provisioning in different groups of banks, specifically, in non-traded standalone community banks, non-traded community banks that are part of bank holding companies, and in traded banks. Panel A shows the result of loan loss provisioning in non-traded standalone community banks. Except for column 1, all other four columns show coefficients on X are significant and positive, indicating the income-smoothing behavior in non-traded standalone community banks. Panel B shows the result of loan loss provisioning in non-traded community banks that are part of bank holding companies. In all five models, X loads with significant and positive coefficient, providing strong evidence that income-smoothing behavior exists in non-traded community banks that are part of bank holding companies. Panel C reports the result of loan loss provisioning in traded community banks. The result shows that all the coefficients on X have insignificant loadings, except in column 5, X loads with significant (at 10%) level and positive coefficient. Result of Table 6.5 indicates that income-smoothing behavior does not exist in traded community banks. One of the possible reasons could be the stricter scrutiny. As a public traded community banks, the banks not only under the supervision of bank regulators, but also under the scrutiny of SEC, analysts and stock investors. Table 6.5 also provides insight into the insignificant result of the effect of bank holding companies in loan loss provisioning. Publicly traded community banks are less aggressive in income smoothing than non-traded community banks, however, only small portion of banks that are part of bank holding companies are publicly traded. Combining the results from Table 6.4 and Table 6.5, we do not have evidence supports the argument that diversified business of bank holding companies leads to a less aggressive income smoothing.

Table 6.5: Loan loss provisioning in different groups of banks

Panel A: loan loss provisioning in non-traded standalone community banks					
	(Laeven and Majnoni, 2003)	(Liu and Ryan, 2006)	(Kanagaretnam etal., 2010)	(Bushman and Williams, 2012)	(Beck and Narayanmoorthy, 2013)
VARIABLES	PLLN_A	PLLN_A	PLLN_A	PLLN_A	PLLN_A
X	2.553	11.748***	5.421***	5.174**	2.983***
	(2.047)	(3.929)	(1.125)	(2.503)	(1.036)
HIGH_ROA		-0.385***			
		(0.025)			

X_HOM		16.944**			
		(7.194)			
X_ROA		-9.389***			
		(3.449)			
LAG1_ALL			-34.685***		-35.258***
			(2.681)		(2.434)
LAG1_NPL			4.994***		
			(0.548)		
NLCO			93.998***		
			(1.668)		
DNPA		8.341***	9.027***	9.782***	7.728***
		(0.855)	(0.673)	(1.085)	(0.577)
DLOAN	-		0.213**		
	(0.118)		(0.098)		
PERIOD1	-	-0.267***	-0.104***	-	-0.157***
	(0.024)	(0.018)	(0.011)	(0.026)	(0.013)
PERIOD3	-	-0.303***	-0.095***	-	-0.111***
	(0.025)	(0.020)	(0.011)	(0.021)	(0.012)
DGDP	-			-0.007	
	(0.005)			(0.006)	
CAP_EA		-5.742***			
		(0.230)			
LEAD_DNPA				-1.763*	
				(0.966)	
LAG1_DNPA				13.856**	
				(0.949)	
LAG2_DNPA				9.542***	
				(0.727)	
SIZE				0.110	-0.015
				(0.067)	(0.022)
LAG1_CAP_EA				1.030*	
				(0.552)	
GLCO					96.622***
					(1.596)
INLOAN					0.640**
					(0.276)
COMLOAN					0.788***
					(0.148)
CSRET					0.037
					(0.047)
Constant	0.747***	1.280***	0.339***	-0.955	0.496*
	(0.029)	(0.072)	(0.025)	(0.797)	(0.272)
Observations	13,592	13,592	11,232	7,757	13,592
R-squared	0.148	0.278	0.758	0.282	0.736

Number of banks	2,431	2,431	2,099	1,634	2,431
R2 within	0.148	0.278	0.758	0.282	0.736
R2 overall	0.133	0.247	0.735	0.169	0.726
R2 between	0.171	0.309	0.764	0.0927	0.743
F-stat	97.20	124.1	654.4	58.54	623.6
Prob > F	0	0	0	0	0

Panel B: loan loss provisioning in non-traded community banks that are part of bank holding companies

	(Laeven and Majnoni, 2003)	(Liu and Ryan, 2006)	(Kanagaretnam etal., 2010)	(Bushman and Williams, 2012)	(Beck and Narayanmoorthy, 2013)
VARIABLES	PLLN_A	PLLN_A	PLLN_A	PLLN_A	PLLN_A
X	5.793***	21.313***	5.099***	2.989***	4.458***
	(1.047)	(1.988)	(0.474)	(1.042)	(0.493)
HIGH_ROA		-0.562***			
		(0.016)			
X_HOM		10.182***			
		(2.572)			
X_ROA		-			
		(1.956)			
LAG1_ALL			-32.356***		-30.474***
			(1.052)		(1.287)
LAG1_NPL			4.796***		
			(0.405)		
NLCO			98.426***		
			(0.759)		
DNPA		8.753***	9.529***	12.078**	8.046***
		(0.428)	(0.309)	(0.518)	(0.260)
DLOAN	-		0.100***		
	(0.054)		(0.029)		
PERIOD1	-	-0.278***	-0.090***	-	-0.124***
	(0.010)	(0.007)	(0.004)	(0.011)	(0.005)
PERIOD3	-	-0.234***	-0.080***	-	-0.102***
	(0.010)	(0.008)	(0.004)	(0.009)	(0.005)
DGDP	-			0.005*	
	(0.002)			(0.003)	
CAP_EA		-6.309***			
		(0.272)			
LEAD_DNPA				-	
				(0.419)	
LAG1_DNPA				14.725**	
				(0.466)	
LAG2_DNPA				10.985**	

				(0.360)	
SIZE				0.012	0.022***
				(0.017)	(0.007)
LAG1_CAP_EA				-0.452*	
				(0.260)	
GLCO					99.351***
					(0.715)
INLOAN					0.141
					(0.087)
COMLOAN					0.348***
					(0.046)
CSRET					0.053**
					(0.021)
Constant	0.709***	1.509***	0.312***	0.412**	0.021
	(0.016)	(0.034)	(0.012)	(0.210)	(0.091)
Observations	56,683	56,683	51,121	40,288	56,683
R-squared	0.191	0.371	0.812	0.317	0.788
Number of banks	6,191	6,191	5,886	5,226	6,191
R2 within	0.191	0.371	0.812	0.317	0.788
R2 overall	0.141	0.346	0.693	0.280	0.789
R2 between	0.0702	0.352	0.212	0.306	0.823
F-stat	559.3	736.1	4774	397.1	3289
Prob > F	0	0	0	0	0

Panel C: loan loss provisioning in traded banks

	(Laeven and Majnoni, 2003)	(Liu and Ryan, 2006)	(Kanagaretnam etal., 2010)	(Bushman and Williams, 2012)	(Beck and Narayanmoorthy, 2013)
VARIABLES	PLLN_A	PLLN_A	PLLN_A	PLLN_A	PLLN_A
X	-2.163	4.164	2.553	-2.104	3.304*
	(3.839)	(4.808)	(2.024)	(3.880)	(1.939)
HIGH_ROA		-0.716***			
		(0.067)			
X_HOM		27.990***			
		(8.957)			
X_ROA		-3.829			
		(5.396)			
LAG1_ALL			-20.743**		-23.779***
			(8.745)		(8.633)
LAG1_NPL			2.627*		
			(1.592)		
NLCO			103.385***		
			(2.614)		

DNPA		14.695***	10.930***	18.984**	10.980***
		(1.627)	(1.130)	(2.263)	(1.223)
DLOAN	-		0.141*		
	(0.140)		(0.082)		
PERIOD1	-	-0.458***	-0.140***	-	-0.171***
	(0.045)	(0.032)	(0.016)	(0.045)	(0.018)
PERIOD3	-	-0.226***	-0.151***	-	-0.179***
	(0.045)	(0.032)	(0.016)	(0.053)	(0.020)
DGDP	-0.017**			0.007	
	(0.008)			(0.009)	
CAP_EA		-8.704***			
		(1.035)			
LEAD_DNPA				-2.703*	
				(1.479)	
LAG1_DNPA				20.396**	
				(2.914)	
LAG2_DNPA				15.638**	
				(1.908)	
SIZE				-0.074	-0.022
				(0.061)	(0.022)
LAG1_CAP_EA				-0.496	
				(0.921)	
GLCO					103.368***
					(3.138)
INLOAN					0.002
					(0.265)
COMLOAN					0.180
					(0.191)
CSRET					0.067
					(0.073)
Constant	1.167***	2.067***	0.313***	1.707**	0.607*
	(0.061)	(0.118)	(0.085)	(0.791)	(0.334)
Observations	4,355	4,355	3,792	2,727	4,355
R-squared	0.296	0.519	0.873	0.487	0.852
Number of banks	776	776	705	515	776
R2 within	0.296	0.519	0.873	0.487	0.852
R2 overall	0.227	0.428	0.881	0.378	0.861
R2 between	0.218	0.408	0.894	0.190	0.893
F-stat	76.55	102.1	827.3	62.89	588.3
Prob > F	0	0	0	0	0

PLLN_A: Percentage of Loan loss provisions for the year over lagged total assets; X: Earnings after tax plus loan loss provisions over lagged total assets. HIGH_ROA: dummy variable equals to 1 if a bank's ROA exceeds the median ROA of all banks of the year. X_HOM: The interaction between variable X and HOM_PER (the percentage of homogeneous loans scaled by lagged total asset). X_ROA: The interaction between variable X and HIGH_ROA (dummy variable equals to 1 if a bank's ROA exceeds the median ROA of all banks of the year). DLOAN: The change in total outstanding loans scaled by lagged total assets; PERIOD1: Dummy variable equals to 1 if it is year before 2008; PERIOD3: Dummy variable equals to 1 if it is year after 2010; DGDP: The change in GDP; DNPA: The change in the nonperforming assets scaled by lagged total assets; CAP_EA: Equity to asset ratio; LAG1_ALL: Allowance at the end of last year scaled by lagged total assets; LAG1_NPL: Non-performing loans at the end of last year; NLCO: Net loan charge-offs on loans and leases; LEAD_DNPA: One year ahead DNPA; LAG1_DNPA: First lag of DNPA; LAG2_DNPA: Second lag of DNPA; SIZE: Logged lagged total assets in thousands of dollars; LAG1_CAP_EA: Equity to asset ratio at the end of the year; GLCO: Gross loan charge-offs on loans and leases; INLOAN: Loans to individuals for household, family, and other personal expenditures scaled by lagged total assets; COMLOAN: Commercial and industrial loans scaled by lagged total assets; CSRET: The yearly return on Case-Shiller U.S. National Home Price Index from Federal Reserve Economic Data; BHC: Dummy variable equals to 1 if the community bank is part of bank holding company; X_BHC: Interaction between variable X and BHC.

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6.6 reports the result of the local economic lead indicator. LEAD_3M loads with negative and significant (at 1% level) coefficients in all five models. This result strongly suggests that the local economic indicator strongly explains the loan loss provisions in community banks, supporting our hypothesis 3. This result is also consistent with the literature that local economic conditions affect community banks' performance, consistent with the findings of Meyer and Yeager (2001) and Daly et al. (2003). X also loads with positive and significant (at 1% level) in all five models, strongly supports our hypothesis 1. X_BHC in table 6.6 loads with similar coefficients of table 6.4, consistent with the results in table 6.4. The control variables are similar to what presented in Table 6.3.

Table 6.6: Loan loss provisions and local economic lead indicator

VARIABLES	(Laeven and Majnoni, 2003) PLLN_A	(Liu and Ryan, 2006) PLLN_A	(Kanagaretnam etal., 2010) PLLN_A	(Bushman and Williams, 2012) PLLN_A	(Beck and Narayanmoorthy, 2013) PLLN_A
X	3.580**	18.621**	4.474***	4.485***	4.743***
	(1.473)	(1.934)	(0.744)	(1.728)	(0.737)
X_BHC	0.335	-2.324*	-0.894	-1.975	-0.806
	(1.438)	(1.361)	(0.734)	(1.742)	(0.712)
LEAD_3M	-	-	-0.434***	-	-0.733***
	(0.206)	(0.185)	(0.113)	(0.203)	(0.110)
HIGH_ROA		-			
		(0.013)			
X_ROA		-			
		(1.592)			
LAG1_ALL			-27.682***		-30.108***
			(1.239)		(1.293)
LAG1_NPL			0.180		
			(0.247)		
NLCO			102.050***		
			(0.653)		
DNPA		9.114***	7.552***	11.803**	8.239***
		(0.374)	(0.268)	(0.449)	(0.238)
DLOAN	-		0.076***		
	(0.046)		(0.029)		
PERIOD1	-	-	-0.105***	-	-0.118***
	(0.008)	(0.007)	(0.004)	(0.008)	(0.005)
PERIOD3	-	-	-0.083***	-	-0.089***
	(0.009)	(0.007)	(0.004)	(0.008)	(0.004)
CAP_EA		-			
		(0.229)			
LEAD_DNPA				-	
				(0.360)	
LAG1_DNPA				14.788**	
				(0.407)	
LAG2_DNPA				11.013**	
				(0.316)	
SIZE				0.019	0.011
				(0.016)	(0.007)
LAG1_CAP_EA				-0.265	
				(0.220)	
GLCO					99.078***
					(0.655)

INLOAN					0.195**
					(0.082)
COMLOAN					0.420***
					(0.044)
Constant	0.738***	1.469***	0.343***	0.318	0.148*
	(0.013)	(0.029)	(0.014)	(0.194)	(0.089)
Observations	74,630	74,630	66,145	50,772	74,630
R-squared	0.199	0.365	0.803	0.327	0.784
Number of banks	8,485	8,485	7,962	6,888	8,485
R2 within	0.199	0.365	0.803	0.327	0.784
R2 overall	0.147	0.332	0.804	0.280	0.787
R2 between	0.108	0.333	0.848	0.254	0.822
F-stat	607.6	740.7	4854	459.7	3913
Prob > F	0	0	0	0	0

PLLN_A: Percentage of Loan loss provisions for the year over lagged total assets; X: Earnings after tax plus loan loss provisions over lagged total assets. HIGH_ROA: dummy variable equals to 1 if a bank's ROA exceeds the median ROA of all banks of the year. X_HOM: The interaction between variable X and HOM_PER (the percentage of homogeneous loans scaled by lagged total asset). X_ROA: The interaction between variable X and HIGH_ROA (dummy variable equals to 1 if a bank's ROA exceeds the median ROA of all banks of the year). DLOAN: The change in total outstanding loans scaled by lagged total assets; PERIOD1: Dummy variable equals to 1 if it is year before 2008; PERIOD3: Dummy variable equals to 1 if it is year after 2010; DNPA: The change in the nonperforming assets scaled by lagged total assets; CAP_EA: Equity to asset ratio; LAG1_ALL: Allowance at the end of last year scaled by lagged total assets; LAG1_NPL: Non-performing loans at the end of last year; NLCO: Net loan charge-offs on loans and leases; LEAD_DNPA: One year ahead DNPA; LAG1_DNPA: First lag of DNPA; LAG2_DNPA: Second lag of DNPA; SIZE: Logged lagged total assets in thousands of dollars; LAG1_CAP_EA: Equity to asset ratio at the end of the year; GLCO: Gross loan charge-offs on loans and leases; INLOAN: Loans to individuals for household, family, and other personal expenditures scaled by lagged total assets; COMLOAN: Commercial and industrial loans scaled by lagged total assets; BHC: Dummy variable equals to 1 if the community bank is part of bank holding company; LEAD_3M: Last three months average at the end of a year of the state leading index from Federal Reserve Bank of Philadelphia scaled by 100; BHC_LEAD_3M: Interaction between variable LEAD_3M and BHC.

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6.7 shows the results of dynamic income smoothing proposed by Liu and Ryan (2006), the effect of being part of a bank holding company and the influence of local economic indicators. Dynamic income smoothing process has two parts. Panel A shows the part of recoveries and lagged gross loan charge-offs. In Panel A, we are interested in the coefficient of LAG1_GLCO, expecting the loadings on LAG1_GLCO to be significantly positive. Columns 1-4 show different models which include different local economic indicators. However, the results of columns 1-4 are similar. In column 1, we regress recovery on variables from Liu and Ryan (2006), and we do not include any economic variable. It turns out that LAG1_GLCO loads with a positive and significant (at 1% level) coefficient. In column 2, we add DCOIN into the model in column 1, and we find the same result on LAG1_GLCO, an we also find DCOIN loads with a negative and significant (at 5% level) coefficient. In column 3, we add LEAD_3M instead of DCOIN in column 2, and we find LEAD_3M loads with a negative and significant (at 1% level) coefficient. In column 4, we replace LEAD_3M in column 3 with LEAD_12M, and we find an insignificant result of LEAD_12M, which is contrary to our expectation. This positive association between LAG1_GLCO and REC shows when a community bank recorded more charge-offs, in order to keep their loan loss allowance flat, they will have to recover more loans. And the coefficient shows the recovered loans are on average 3.2% of the past gross loan charge-offs.

Table 6.7: Dynamic income smoothing regressions

Panel A: Recoveries and lagged gross loan charge-offs				
	(1)	(2)	(3)	(4)
VARIABLES	RECOVER	RECOVER	RECOVER	RECOVER
LAG1_GLCO	0.032***	0.032***	0.032***	0.032***
	(0.004)	(0.004)	(0.004)	(0.004)
BHC	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
BHC_LGLCO	0.006	0.006	0.006	0.006
	(0.004)	(0.004)	(0.004)	(0.004)
LAG1_CAP_EA	0.001	0.001	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
DNPA	-0.006***	-0.006***	-0.006***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
LAG1_DNPA	-0.003***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
LAG2_DNPA	-0.003***	-0.003***	-0.003***	-0.003***

	(0.001)	(0.001)	(0.001)	(0.001)
LAG3_DNPA	-0.001*	-0.001*	-0.001*	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
SIZE	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
PERIOD1	-0.000***	-0.000*	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
PERIOD3	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
DCOIN		-0.000**		
		(0.000)		
LEAD_3M			-0.001***	
			(0.000)	
LEAD_12M				-0.000
				(0.000)
Constant	0.004***	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	50,772	50,772	50,772	50,772
R-squared	0.078	0.078	0.078	0.078
Number of banks	6,888	6,888	6,888	6,888
Firm FE	Yes	Yes	Yes	Yes
Firm cluster	Yes	Yes	Yes	Yes
R2 within	0.0781	0.0782	0.0784	0.0782
R2 overall	0.0759	0.0764	0.0758	0.0754
R2 between	0.0889	0.0897	0.0886	0.0881
F-stat	94.31	87.41	86.49	86.80
Prob > F	0	0	0	0

Panel B: Gross charge-offs and recoveries

	(1)	(2)	(3)	(4)
VARIABLES	GLCO	GLCO	GLCO	GLCO
REC	0.814***	0.813***	0.813***	0.813***
	(0.051)	(0.051)	(0.051)	(0.051)
BHC	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
BHC_REC	-0.006	-0.005	-0.005	-0.005
	(0.054)	(0.054)	(0.054)	(0.054)
CAP_EA	-	-	-	-
	(0.001)	(0.001)	(0.001)	(0.001)
PLLN_A	0.007***	0.007***	0.007***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)
LAG1_ALL	0.336***	0.336***	0.336***	0.336***
	(0.012)	(0.012)	(0.012)	(0.012)
DNPA	-	-	-	-

	(0.002)	(0.002)	(0.002)	(0.002)
SIZE	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
PERIOD1	-	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
PERIOD3	-	-	-	-
	(0.000)	(0.000)	(0.000)	(0.000)
DCOIN		-0.001**		
		(0.000)		
LEAD_3M			-	
			(0.001)	
LEAD_12M				-
				(0.001)
Constant	-	-	-	-
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	74,630	74,630	74,630	74,630
R-squared	0.809	0.809	0.809	0.809
Number of banks	8,485	8,485	8,485	8,485
Firm FE	Yes	Yes	Yes	Yes
Firm cluster	Yes	Yes	Yes	Yes
R2 within	0.809	0.809	0.809	0.809
R2 overall	0.814	0.814	0.814	0.814
R2 between	0.849	0.848	0.848	0.848
F-stat	3776	3435	3435	3450
Prob > F	0	0	0	0

PLLN_A: Percentage of Loan loss provisions for the year over lagged total assets; REC: Recoveries on loans and leases; GLCO: Gross loan charge-offs on loans and leases; LAG1_GLCO: First lag of GLCO; CAP_EA: Equity to asset ratio; LAG1_CAP_EA: Equity to asset ratio at the end of the year; DNPA: The change in the nonperforming assets scaled by lagged total assets; LAG1_DNPA: First lag of DNPA; LAG2_DNPA: Second lag of DNPA; LAG3_DNPA: Third lag of DNPA; PERIOD1: Dummy variable equals to 1 if it is year before 2008; PERIOD3: Dummy variable equals to 1 if it is year after 2010; SIZE: Logged lagged total assets in thousands of dollars; DCOIN: The yearly change in the state coincident index from Federal Reserve Bank of Philadelphia scaled by 100; LEAD_3M: Last three months average at the end of a year of the state leading index from Federal Reserve Bank of Philadelphia scaled by 100. LEAD_12M: Last twelve months average at the end of a year of the state leading index from Federal Reserve Bank of Philadelphia scaled by 100; LAG1_ALL: Allowance at the end of last year scaled by lagged total assets; BHC: Dummy variable equals to 1 if the community bank is part of bank holding company; BHC_REC: interaction between variable BHC and REC.

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Panel B represents the other side of the story related to concurrent gross charge-offs and recoveries. The result from Panel B shows 1 percentage point increase in recoveries would increase gross loan charge-offs by 0.814 percentage points. This positive association between recoveries and charge-offs indicates that if a community bank has more recoveries, it has to record more charge-offs to keep loan loss allowance relatively stable. Besides, local economic indicators added in the models load with negative and significant coefficients. Results from Panel A and Panel B strongly suggests a dynamic income smoothing process in community banks, supporting our hypothesis 4.

Table 6.7 also reports any possible effect of being part of a bank holding company in dynamic income smoothing process. However, we do not observe any significant effect, since the coefficients on BHC and the interaction between BHC and LAG1_GLCO (BHC_LGLCO) are insignificant in the recovery regressions in panel A, and the coefficients on BHC and BHC_REC are insignificant in the gross loan charge-offs regressions in panel B.

Table 6.8 reports the result of loan loss allowance regressions. We are interested in the connection between loan loss allowance and local economic indicators and we find lead indicators, LEAD_3M and LEAD_12M, load with insignificant coefficients. The result indicates that future economic situation does not affect how community banks plan their loan loss allowance. We also find change in the coincident indicator, DCOIN, loads with a significantly positive coefficient. This also implies that the loan loss allowance account is more associated with the past when it should be more associated with the future. From this result, we can conclude the loan loss allowance estimation in banks is not forward-looking.

Table 6.8: Allowance and economic indicators

VARIABLES	(1) ALL	(2) ALL	(3) ALL	(4) ALL
LAG1_GLCO	0.114***	0.116***	0.118***	0.118***
	(0.013)	(0.013)	(0.013)	(0.013)
BHC	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
BHC_LGLCO	0.020	0.020	0.020	0.020
	(0.014)	(0.014)	(0.014)	(0.014)
NAL	0.139***	0.138***	0.137***	0.137***
	(0.003)	(0.003)	(0.003)	(0.003)
INLOAN	0.003***	0.003**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
COMLOAN	0.007***	0.007***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
SIZE	-	-	-	-
	(0.000)	(0.000)	(0.000)	(0.000)
CSRET	-0.000*			
	(0.000)			
DUNRATE	-			
	(0.002)			
DCOIN		0.001***		
		(0.000)		
LEAD_3M			0.001	
			(0.001)	
LEAD_12M				0.000
				(0.002)
Constant	0.013***	0.012***	0.012***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	66,145	66,145	66,145	66,145
R-squared	0.311	0.310	0.310	0.310
Number of banks	7,962	7,962	7,962	7,962
R2 within	0.311	0.310	0.310	0.310
R2 overall	0.355	0.357	0.358	0.358
R2 between	0.438	0.442	0.444	0.444
F-stat	390.7	436.9	438.2	441.7
Prob > F	0	0	0	0

LAG1_GLCO: First lag of gross loan charge-offs on loans and leases; BHC: Dummy variable equals to 1 if the community bank is part of bank holding company; BHC_LGLCO: The interaction between variable BHC and lagged GLCO; NAL: Nonaccrual loans, leases and other assets; INLOAN: Loans to individuals for household, family, and other personal expenditures

scaled by lagged total assets; COMLOAN: Commercial and industrial loans scaled by lagged total assets; SIZE: Logged lagged total assets in thousands of dollars; CSRET: The yearly return on Case-Shiller U.S. National Home Price Index from Federal Reserve Economic Data; DUNRATE: The yearly change in the unemployment rate from Bureau of Labor Statistics; DCOIN: The yearly change in the state coincident index from Federal Reserve Bank of Philadelphia scaled by 100; LEAD_3M: Last three months average at the end of a year of the state leading index from Federal Reserve Bank of Philadelphia scaled by 100; LEAD_12M: Last twelve months average at the end of a year of the state leading index from Federal Reserve Bank of Philadelphia scaled by 100.

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

CHAPTER 7

CONCLUSIONS

This study examines income-smoothing behavior in community banks, a topic barely covered in banking earning management literature. Specifically, we examine whether community banks smooth their income through loan loss provisioning.

We follow the multidimensional approach proposed by FDIC community banking study (2012) to construct our community banks data set. This new approach enables us to cover large commercial banks and bank holding companies which are excluded in previous community banking studies. In addition, community banks under the new approach are more responsive to local events, which enables us to see the relationship between local economic conditions and loan loss provisions. Our sample includes 8485 individual community banks and 74630 bank-year observations.

Overall, we find strong evidence that income smoothing does exist in community banks. While the motivations for income smoothing in community banks might be different from those of large commercial banks, we find how community banks overwhelmingly use loan loss provisioning to smooth their income. While our dataset does not allow us to directly test the community banks' motivations for smoothing income, perhaps a) executive compensation is a motivation for their income smoothing as managers may be compensated for steady stream of earnings and b) urge to lower cost of external financing as raising external fund is as important in community banks as it is in large commercial banks. However, we do not find evidence supports the argument that diversified business of bank holding companies leads to a less aggressive income smoothing. We discover that stricter scrutiny from regulatory bodies, analysts, and investors has strong effect in income smoothing of community banks. Furthermore, we find that state-level local economic indicators significantly explain variation in loan loss provisioning of community banks. This result reinforces the argument that the local economic variations affect performance of community banks. Finally, we test the dynamic income smoothing proposed by Liu and Ryan (2006), and we find evidence that dynamic income smoothing exists in community banks. That is to say, banks accelerate loan charge-offs and recover them the next year and record more loan charge-offs when they have more loan recoveries at the same year in order to keep the allowance flat.

Our findings have implications for regulators when they intend to make new policies on community banks due to their unique and important role in the local economy.

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